Detecting Informative Tweets during Disaster using Deep Neural Networks

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***Abstract*—The post on information tweets increased as increase of data posted on social media during a disaster. Informative tweets can give the useful information about affected people, infrastructure damage, humanitarian organizations, etc. This paper proposed a method for classifying the informative and non-informative tweets during a disaster. The proposed approach is based on the Convolutional Neural Network (CNN) and Artificial Neural Network (ANN). CNN is used for feature extraction and ANN used as a classifier for classifying the tweets. The proposed method is tested on a real-time twitter dataset such as Hurricane Harvey 2017. Proposed method outperforms the existing methods regarding precision, recall, F1-score and accuracy.**

***Index Terms*—Convolution Neural Network, Artificial Neural Network, Disaster**

I. Introduction

Nowadays, a significant amount of data is posted on micro-blogging platforms during natural and human-made disasters. Data may be in the form of audio, image, text, video, etc. Twitter is one of the vital micro-blogging platforms where a large amount of information is posted in the form of tweets during disasters. Tweets contain the informative and non-informative words related to disaster. Informative tweets gives information either it is helpful to victims or humanitarian organizations require details about the the need of the affected people, injured or dead people, infrastructure damage, availability of resources, etc., [1] during a disaster. Non-informative tweets do not give any useful information about the disaster. Therefore, detecting the informative tweets during a disaster is a challenging task. Table 1 shows some examples of informative and non-informative tweets from the dataset [2]. First tweet represents the availability of resource and second tweet represents the need of the resources or help. Both of the tweets come under sub-category of informative tweets.

The authors in [3] used CNN for identifying informative messages during a disaster. They used the flood datasets such as Philippines floods, Colorado floods, Queensland floods, etc. And compared the CNN against SVM and ANN with uni-gram, combination of uni-gram and bi-gram and combination of uni-gram and bi-gram and trigram features. This method doesn't give better accuracy and also the comparison is made with existing methods in terms of accuracy and doesn't not focus on recall, precision and F1-score. Therefore proposed a method with the combination of CNN and ANN for detecting the informative messages during a disaster. And also results are compared with the parameters such as recall, precision and f1-score.

The contributions of this paper are summarized as shown below:

- Proposed a method with combination of CNN and ANN for detecting the informative tweets during a disaster.
- Compared the proposed method with existing methods such as CNN, SVM and ANN with uni-gram, uni-gram and bi-gram, combination of uni-gram and bi-gram and tri-gram features. The proposed method outperforms the existing methods in the parameters of the precision, recall, f1-score and accuracy.

The rest of the paper is as follows. Section 2 describes the related work for the problem. The proposed method is explained in Section 3. Section 4 gives experimental results and analysis. The paper is concluded in Section 5.

II. Related Work

Natural Language Processing (NLP) and Machine learning play a crucial role in classifying the social media posts [4] during a disaster. The authors [5] investigated the misleading information and rumor propagation during a disaster using social media by taking the Chilean earthquake dataset. Non-situational tweets contain the tweets like communal tweets. The communal tweets are posted mostly during a disaster compare to the non-communal tweets. Therefore, the authors in [6] investigated the communal tweets and claims that more popular persons are also posted the communal tweets along with common people. Additional, they have a strongly connected group in a social network. For experimenting the method five disaster datasets such as CShoot, NEQuake, GShoot, PAttack and KFlood are used. In [7], the authors proposed a model for classifying the posts into different categories such as affected people information, infrastructure damage, resources and so on which are useful to the organizations and the victims for accessing them. The authors [8] found that the features such as the presence of wh-words, the presence of numerals discriminating the situational and non-situational information. And constructed a method for summarizing the situational information after classifying the tweets.

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TABLE I
SOME EXAMPLE TWEETS OF INFORMATIVE AND NON-INFORMATIVE

Tweet No	Informative Tweets
1.	RT @DrHipHops: Absolute devastation. Text the word HARVEY to 90999 to make a $10 donation to the @RedCross [URL]
2.	This viral before-and-after photo shows the harrowing damage of California wildfires [URL][URL]
3.	RT @KAKEnews: California wildfires destroy more than 50 structures: [URL] #KAKEnews [URL]
4.	At Least 11 Dead and 100 Missing as Wildfires Rage Across Northern California - Damage and death toll rises as [URL][URL]
	Non-Informative Tweets
5.	@barkbox Harvey #TheDogNotTheStorm is filling a huge hole in our hearts [URL]
6.	@yIleza: When we get back to SCHS after Harvey hits : [URL] [URL].
7.	Thinking of all my California loved ones, friends and colleagues. Please be safe. #wildfires [URL][URL].
8.	Major disaster declaration approved for the state of #California due to #wildfires. [URL] [URL].

Similarly, the authors [9] provided automatic classification method for detecting the tweets related to diseases such as Ebola and MERS. The method used presence of sign/symptoms, the presence of preventive terms, the presence of preventive procedures feature. However, it is not applicable to disaster. In [10], the authors proposed the features such as disaster terms, communication terms, infrastructure damage terms, location terms and so on for detecting the resources which include availability and requirement of resources during a disaster. However, all papers discussed about the different types useful information during a disaster. Hence, it is very important to detect the informative tweets during a disaster. Therefore, proposed a method for detecting the informative tweets during a disaster.

III. METHODOLOGY

This section describes the methods used in the proposed work such as Convolutional Neural Network (CNN) and Artificial Neural Network (ANN).

A. CNN Architecture

CNN architecture is more popular for solving text classification problems [3], [11] due to automatic extraction of features and gives more accuracy. The pre-trained word embeddings such as crisis word embedding, Google word embedding, etc., are available which are used to generate low dimensional word vectors. Word vectors are considered as feature extractors for any text classification problems and achieve better performance.

The CNN architecture used in this work has five layers such as an input layer, a convolution layer, pooling layer, dense layer and an output layer. Crisis word embeddings are used for getting the word vectors for each word in a tweet because these are very large word embeddings which are specially trained from the largest crisis corpus. Let $w_k \in R^i$ be the i dimensional word vector of k^{th} word in a tweet. Let the tweet consists a sequence of words:$w_1, w_2, ...w_n$. Then, the tweet vector is acquired by the Eq 1

$$v_{1:n} = v_1 o v_2 o v_3 .....v_n \tag{1}$$

where o is the concatenation operator, v_k be the corresponding word vector of w_k. Tweet matrix of length TXi is fed as input to the input layer, where T be the number of words in the tweet and i be the dimension. Convolution operation is applied to the tweet matrix for getting the new features by applying different filters to window of h words. Similarly, convolutional features are computed for all the feasible window of h words. Subsequently, convolutional features are fed to the pooling layer. The aim of the pooling layer to get the decisive activation. Max, average, min are the pooling operation. Among them, max pooling operation is utilized in this architecture. Subsequently, results are fed to the dense layer and then finally softmax function is used for predicting the class on a given tweet. ADADELTA [12] optimization technique is used during the training of the CNN. Dropout [13] parameter is used to avoid the over-fitting problem and 25 epochs are used. Batch size is 256 and early stopping criteria are used based on the validation accuracy.

B. Artificial Neural Network

Artificial Neural Network (ANN) is a classifier which gives the best performance for identifying the informative messages during disaster [3]. The ANN is inspired by the working of biological neurons in the brain and central nervous system [14], [15]. The ANN has the layers such as an input layer, hidden layer and output layer. Each layer is represented by one or more neurons. The number of neurons in the input layer depends on the length of the tweet feature vector x. The number of neurons in the hidden layer is an input parameter decided by the user. Finally, the output layer for binary classification problems consists of one neuron. Neurons in the output layer are activated by the non-linear activation functions

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such as sigmoid, hyperbolic tangent (tanh), Rectified Linear Units (ReLU) etc. In this proposed work, ReLU activation function [16] is used because it is more popular in recent time and it is denoted in Eq.s 2 and 3.

$$Re(x) = max(0, x) \tag{2}$$

$$Re(x) = \begin{cases} 0, & \text{if } x < 0 \\ 1, & \text{otherwise} \end{cases} \tag{3}$$

This function eliminates all negative values in the feature values and gives better results. All the neurons are interconnected from one layer to another layer with weighted connections. Initially, random values are assigned as weights for training the model. During training, weights are updated using the back-propagation algorithm [17].

C. Combination of CNN and ANN

A method is proposed to detect the informative tweets during a disaster by combination of the CNN and ANN. In [3], the authors used CNN for identifying messages during a disaster without using feature extraction techniques and it outperforms SVM and ANN with features such as uni-gram, bi-gram and tri-gram. And concluded that ANN performs well than the SVM with feature engineering. Hence, in this work CNN and ANN are used for identifying the informative tweets during a disaster. The output of CNN (i.e) feature score vector is applied as input of ANN to make the model classify well. Then the performance of the proposed method will be increased as compared with ANN with feature engineering and individual CNN. The overview of the proposed method is shown in Fig. 1.

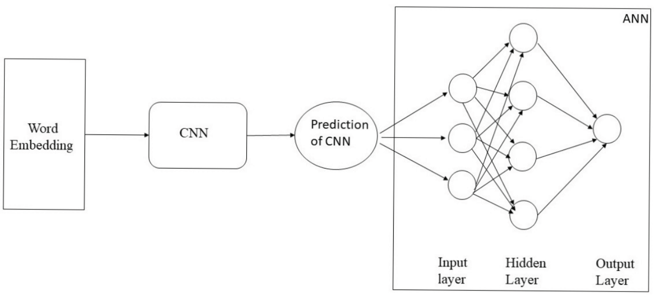

Fig. 1. Overview of the proposed method

IV. Experimental Results and Analysis

Python language, scikit package [18] and keras library [19] are used for implementing machine learning and deep learning models respectively. Datasets, evaluation metrics and performance analysis are described in the forthcoming sections.

A. Datasets

Hurricane Harvey hit Texas in US on August 25, 2017. It is the biggest natural disaster in US. Tweets are collected from August 26, 2017 to September 20, 2017. The authors in [2] provide the annotated data. From that 80% tweets are used for training and 20% tweets are used for testing by balancing the both Informative and non-informative tweets.

B. Evaluation Metrics

Let T_P denotes the True Positive, it is the number of the informative tweets detected correctly, T_N indicates the True Negative which is the number of non-informative tweets detected correctly, F_P denotes the False Positive which is the number of non-informative tweets detected as informative tweets and F_N denotes False Negative which is the number of informative tweets detected as non-informative. The evaluation metrics such as Precision, Recall, F1-score and Accuracy are given in Eq.s 4, 5, 6 and 7 respectively.

- Precision: Precision is calculated as follows.

$$Precision(P) = \frac{T_P}{T_P + F_P} \tag{4}$$

- Recall: Recall is calculated as follows.

$$Recall(R) = \frac{T_P}{T_P + F_N} \tag{5}$$

- F1-score: F1-score is calculated as follows:

$$F1 - score = \frac{2PR}{P + R} \tag{6}$$

- Accuracy: Accuracy is calculated as follows:

$$Accuracy = \frac{T_P + T_N}{T_P + F_P + T_N + F_N} \tag{7}$$

C. Performance analysis

The experimental results are analyzed in this section. SVM classifier with uni-gram, uni-gram and bi-gram features results are presented in Table II for different parameters. Similarly Table III represents result of ANN classifier. SVM and ANN classifier with uni-gram, bi-gram and tri-gram features are shown in Table IV. Table V shows result of CNN. The CNN and ANN are combined and their results are shown in Table VI and existing methods are compared with SVM, ANN gives better accuracy. However, CNN gives the best accuracy among the existing approaches. The proposed approach (combination of CNN and ANN) outperforms than the all existing approaches in the parameters such as the Precision, Recall, F1-score and Accuracy and is shown in Table VII. In the Table VII SVM(1) represents SVM with uni-gram, SVM(2) represents uni-gram and bi-gram, SVM(3) represents uni-gram and bi-gram and tri-gram and similarly representation for ANN(1), ANN(2) and ANN(3) too.

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TABLE II
SVM CLASSIFIER RESULT WITH UNI-GRAM, UNI-GRAM AND BI-GRAM FEATURES

Tweets	Uni-gram				Uni-gram and Bi-gram			
	Precision	**Recall**	**F1-score**	**Accuracy**	**Precision**	**Recall**	**F1-score**	**Accuracy**
Informative	89	18	29	-	76	21	33	-
Non-Informative	54	98	70	-	54	93	69	-
Average	71	58	50	57.65	65	57	51	57.20

TABLE III
ANN CLASSIFIER RESULT WITH UNI-GRAM, UNI-GRAM AND BI-GRAM FEATURES

Tweets	Uni-gram				Uni-gram and Bi-gram			
	Precision	**Recall**	**F1-score**	**Accuracy**	**Precision**	**Recall**	**F1-score**	**Accuracy**
Informative	70	76	73	-	0.00	0.00	0.00	-
Non-Informative	73	67	70	-	50	100	67	-
Average	72	71	71	71.79	25	50	33	50

TABLE IV
SVM AND ANN CLASSIFIER RESULT WITH UNI-GRAM, UNI-GRAM AND BI-GRAM FEATURES

Tweets	SVM classifier				ANN classifier			
	Precision	**Recall**	**F1-score**	**Accuracy**	**Precision**	**Recall**	**F1-score**	**Accuracy**
Informative	75	20	32	-	0.00	0.00	0.0	-
Non-Informative	54	93	68	-	50	100	67	-
Average	64	57	50	56.75	25	50	33	50

TABLE V
PERFORMANCE OF CNN FOR DIFFERENT PARAMETERS

Tweets	Precision	Recall	F1-score	Accuracy
Informative	68	84	75	-
Non-Informative	79	60	68	-
Average	73	72	72	72.07

TABLE VI
PERFORMANCE OF PROPOSED CNN WITH ANN METHOD FOR DIFFERENT PARAMETERS

Tweets	Precision	Recall	F1-score	Accuracy
Informative	77	74	76	-
Non-Informative	75	77	76	-
Average	76	76	76	75.9

V. CONCLUSION

This paper developed a method for detecting the informative tweets during a disaster based on CNN and ANN methods. It is observed that the proposed method gives better performance than the use of CNN and ANN alone. It outperforms the existing methods such as SVM and ANN with uni-gram, uni-gram and bi-gram, uni-gram and bi-gram and tri-gram features. The proposed method achieved better performance in different parameters such as precision, recall, F1-score and accuracy. In future, it can extended for other datasets. The method can be improved by adding more layers and applying other deep learning methods.

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TABLE VII
COMPARISON OF PROPOSED METHOD WITH EXISTING METHODS

Methods	Precision	Recall	F1-score	Accuracy
SVM(1)	71	58	50	57.65
SVM(2)	65	57	51	57.20
SVM(3)	64	57	50	56.75
ANN(1)	72	71	71	71.39
ANN(2)	25	50	33	50
ANN(3)	25	50	33	50
CNN	73	72	72	**72.07**
Proposed Method	76	76	76	**75.9**

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